

Retrieval of Surface Reflectance and LAI Mapping with Data from ALI, Hyperion and AVIRIS

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Objectives

- Develop a simple atmospheric correction method
- Map LAI with the ALI, Hyperion and AVIRIS
- Examine the capabilities of the three sensors for extracting LAI information
- Compare different VI and red-edge parameters for LAI estimation

Study Sites and Data

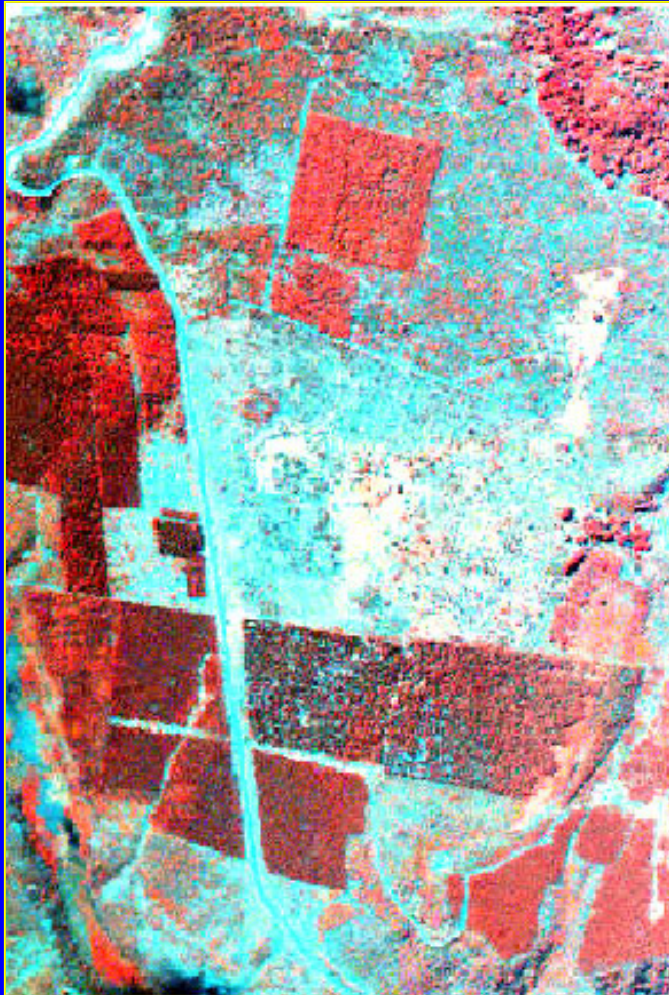
- Study sites:
 - Two sites, in Patagonia, Argentina
 - Flat, semiarid region (show images)
 - Forest plantations, conifer species: PP, LP and Oregon P.
- Spectroradiometric measurements
 - ASD FieldSpec®Pro, covering 0.4 – 2.5 μm
 - Road surface, canopy of young plantation
- LAI measurements
 - 70 LAI plots, with LICOR LAI-2000 PCA
 - Effective LAI

Study Sites and Data (Cont'd)

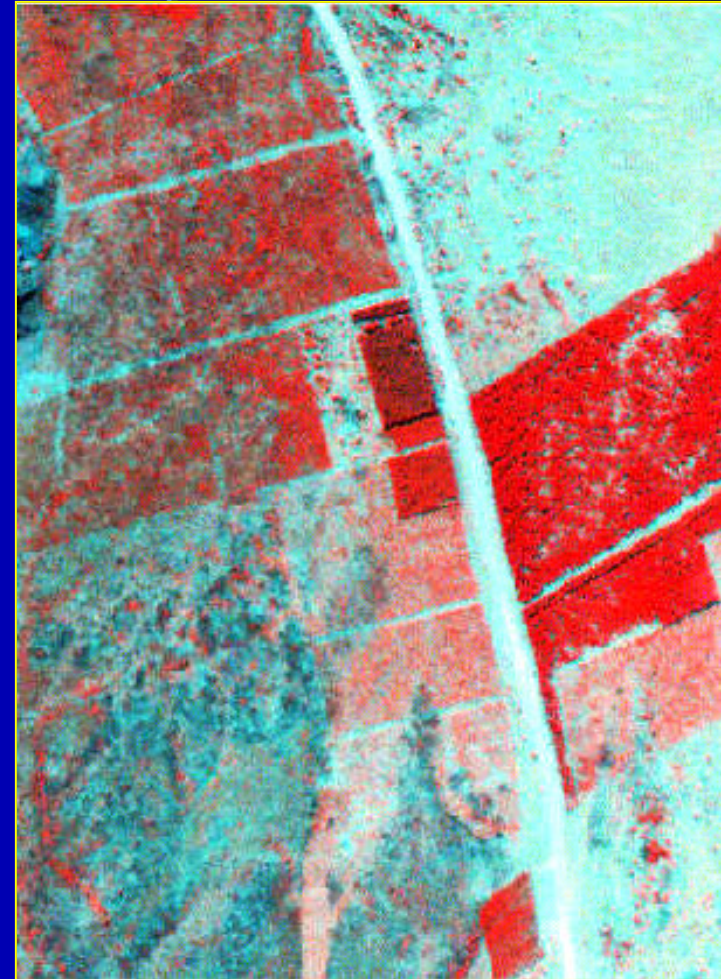
- **ALI: Advanced Land Imager**
Multispectral, 9 bands, 1 panchromatic, 30 m, 3/27/2001
- **Hyperion: Hyperspectral Imager**
 - 220 bands, 0.4 – 2.5 μm
 - 10 nm spectral, 30 m spatial resolution, 3/27/2001
- **AVIRIS: Airborne Visible/InfraRed Imaging Spectrometer**
 - Hyperspectral sensor, altitude of 5029 m
 - 224 bands, 0.4 – 2.5 μm
 - 10 nm spectral, 3.6 m spatial resolution, 2/15/2001

Study Sites (Cont'd)

- Part of the images over the two sites



North

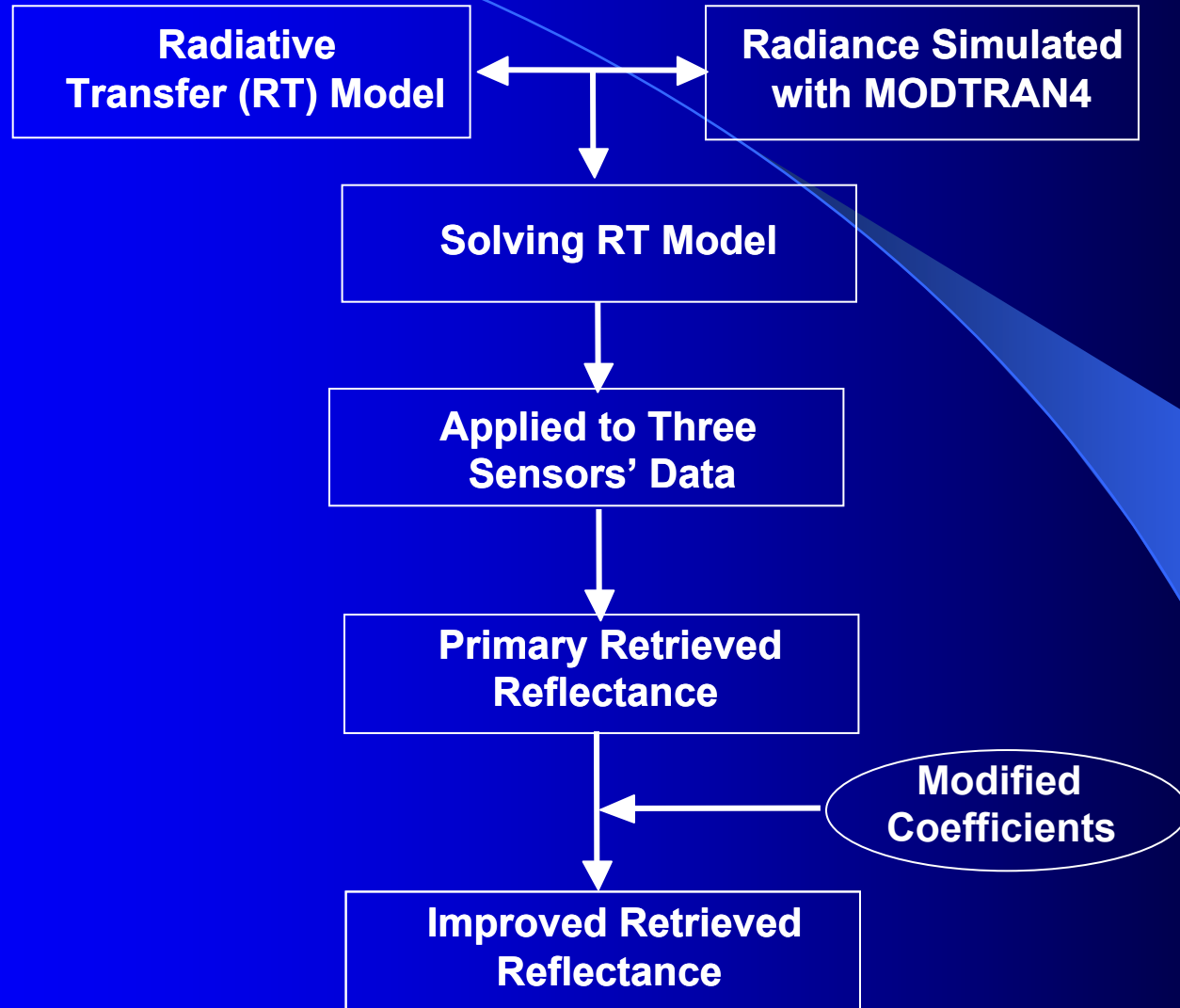


South

Methods

- Atmospheric correction
 - Radiative transfer (RT) model
 - Radiance simulated with MODTRAN4
 - Retrieval surface reflectance
- LAI estimation and mapping
 - Correlation
 - LAI prediction model
 - LAI prediction and mapping

Atmospheric correction: A flowchart



RT model

The at-sensor radiance L can be related to the Lambertian surface reflectance ρ by

$$L = L_a + \frac{T_2 \rho}{1 - S \rho} \frac{E_0 \cos \theta_0}{\pi}$$

Where,

L_a : atmospheric path radiance,

T_2 : two way transmittance for the sun-surface-sensor path,

S : spherical albedo of the atmosphere,

E_0 : exoatmospheric solar irradiance, and

θ_0 : solar zenith angle.

Radiance simulation with MODTRAN4

- Input 3 surface reflectance values: 0.0, 0.3, 0.5
- Water vapor value 0.7 cm/cm²,
- And other necessary parameters for the code
- Output total radiance

Solving RT model

- To solve RT model, need 3 output total radiances simulated with MODTRAN4.
- Solve to obtain L_a , T_2 , and S .

Retrieval of surface reflectance of three sensors' data

- Retrieving surface reflectance: ρ
by RT model with known L_{img} , L_a , T_2 ,
and S for
 - *ALI*
 - *Hyperion*
 - *AVIRIS*

Correlation analysis

- Extract pixel values at 32 LAI measured plots
 - From the retrieved reflectance images
 - 1-4 pixels at each LAI plot from Hyperion and ALI, 25-225 from AVIRIS
- General correlation analysis of spectral bands with LAIs
 - Correlograms of inter-band for Hyperion and AVIRIS
 - Correlation with 32 LAI measurements

LAI prediction models and mapping

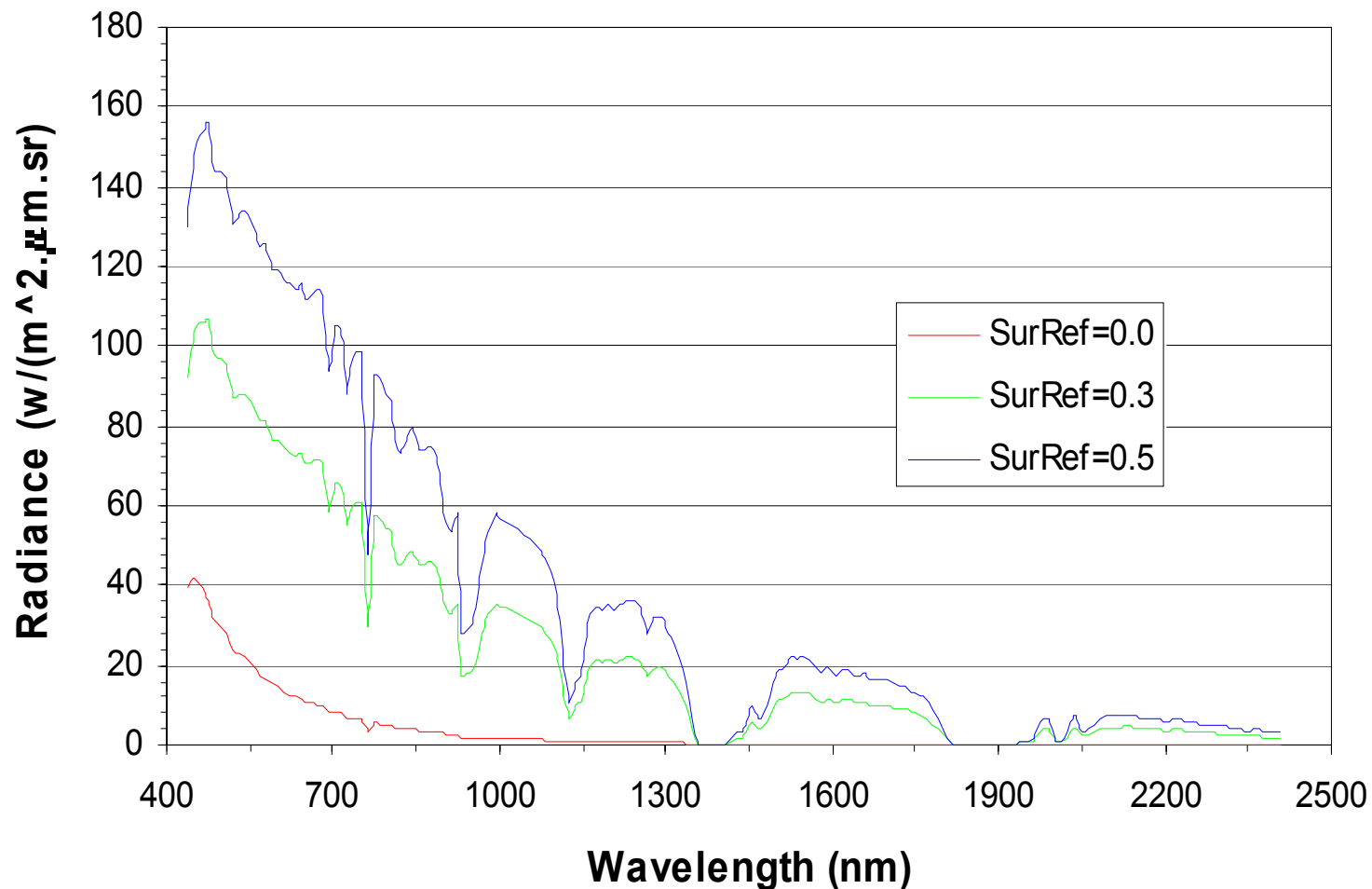
- Select a bunch of bands used for regression analysis based on
 - Correlograms of inter-band of the hyperspectral sensors' data
 - Peak values along the correlation curves
 - Physical meaning (absorption features)

because of redundant information of and inflation phenomenon of R^2 of small observation size (32) relative to large number of bands (~200) of hyperspectral data. Select 12-15 bands from Hyperion and AVIRIS
- Constructing a 6-term LAI prediction model for the three sensors' data
- Predicting pixel-based LAI with 6-term prediction models for three sensors' data

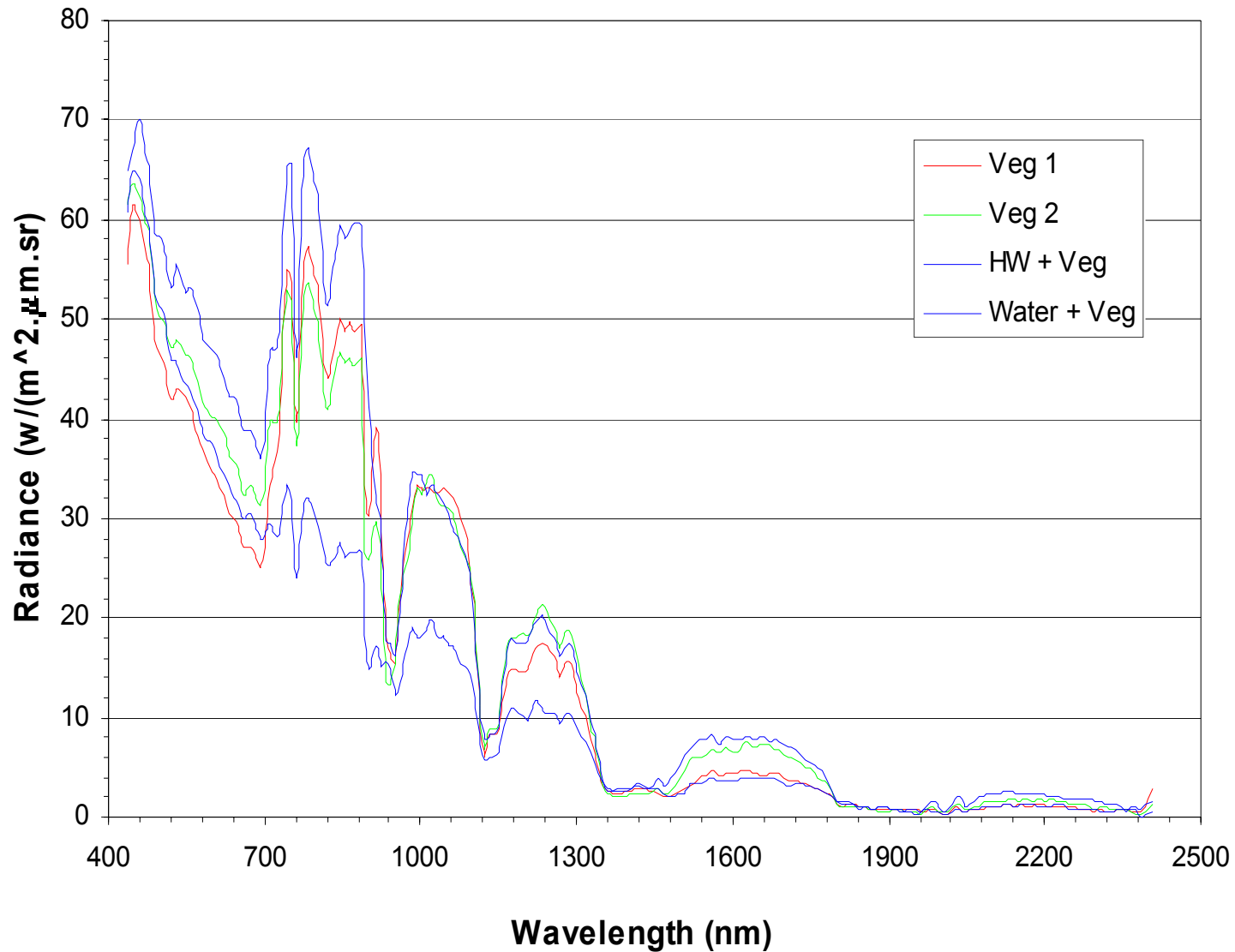
Results and Analysis

- Three total radiances simulated
- Results at different processing stages
- ASD ratio coefficients
- Comparison of retrieved reflectances from the three sensors
- Correlograms of inter-band of hyperspectral data
- Correlation of three sensors with ALI
- Determination of 6-term models
- LAI prediction model (Tables)
- LAI maps

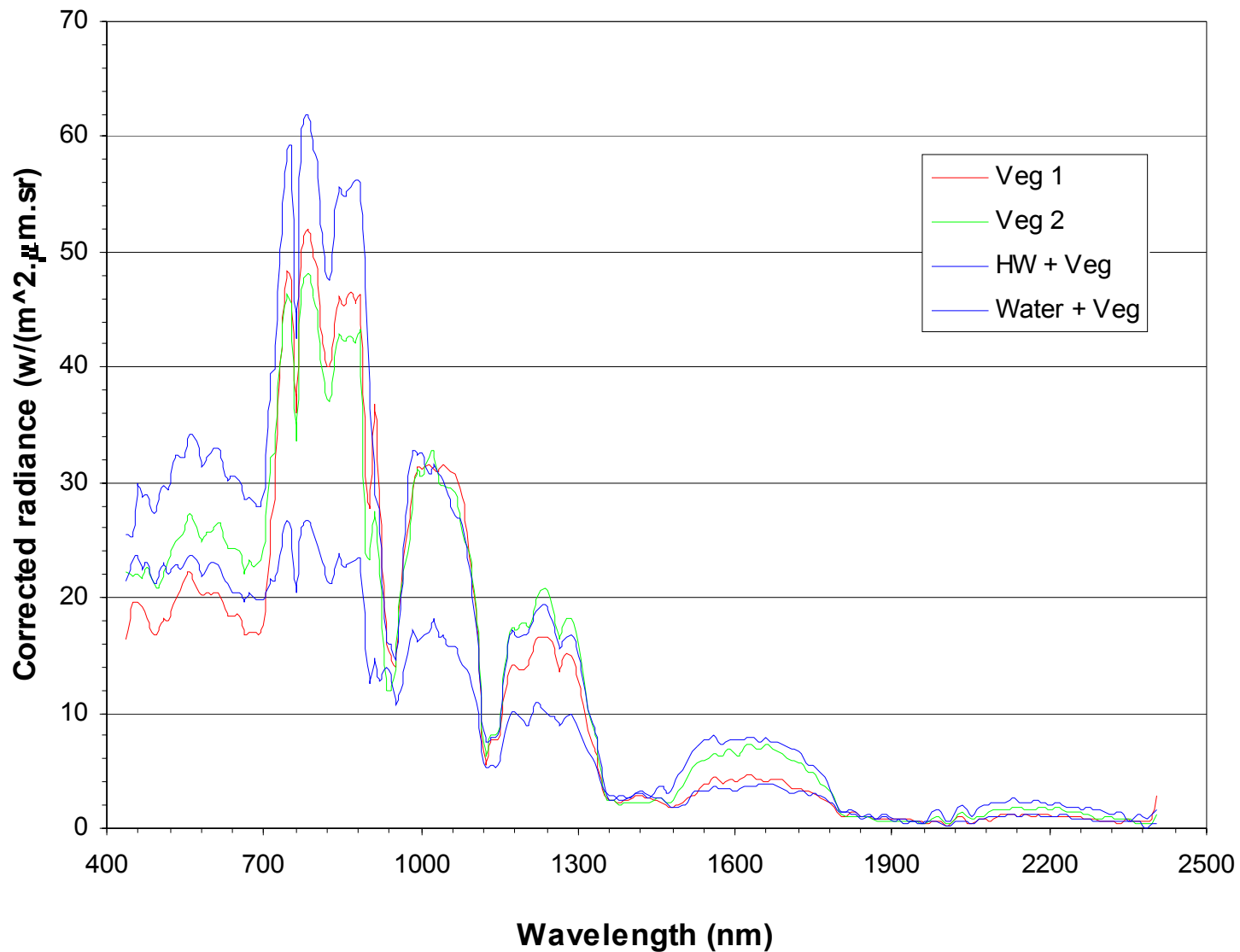
Three total radiances simulated by MODTRAN4,
inputs: ref=0.0, 0.3, 0.5 and wv = 0.7 cm/cm²



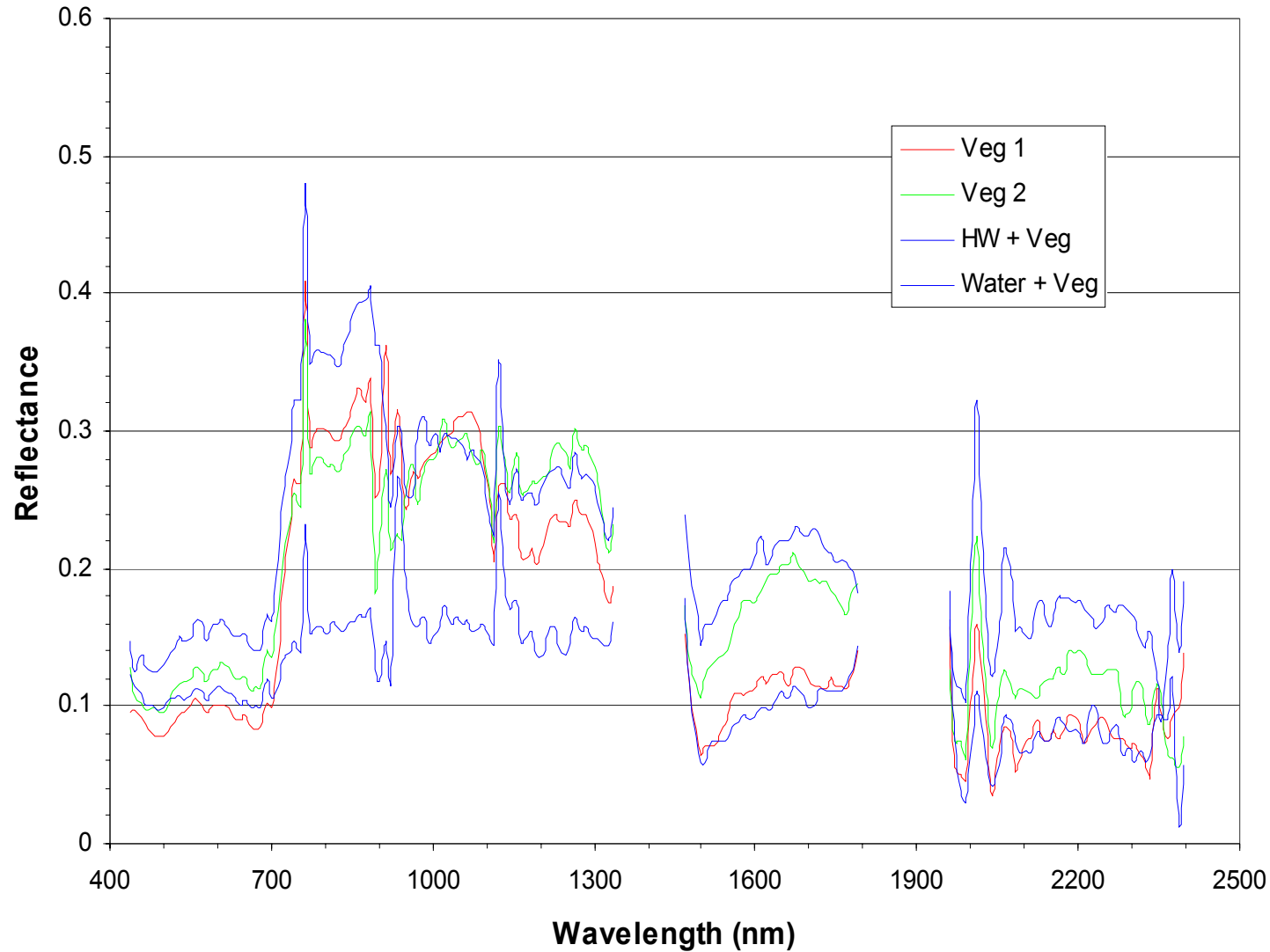
Original radiance of Hyperion



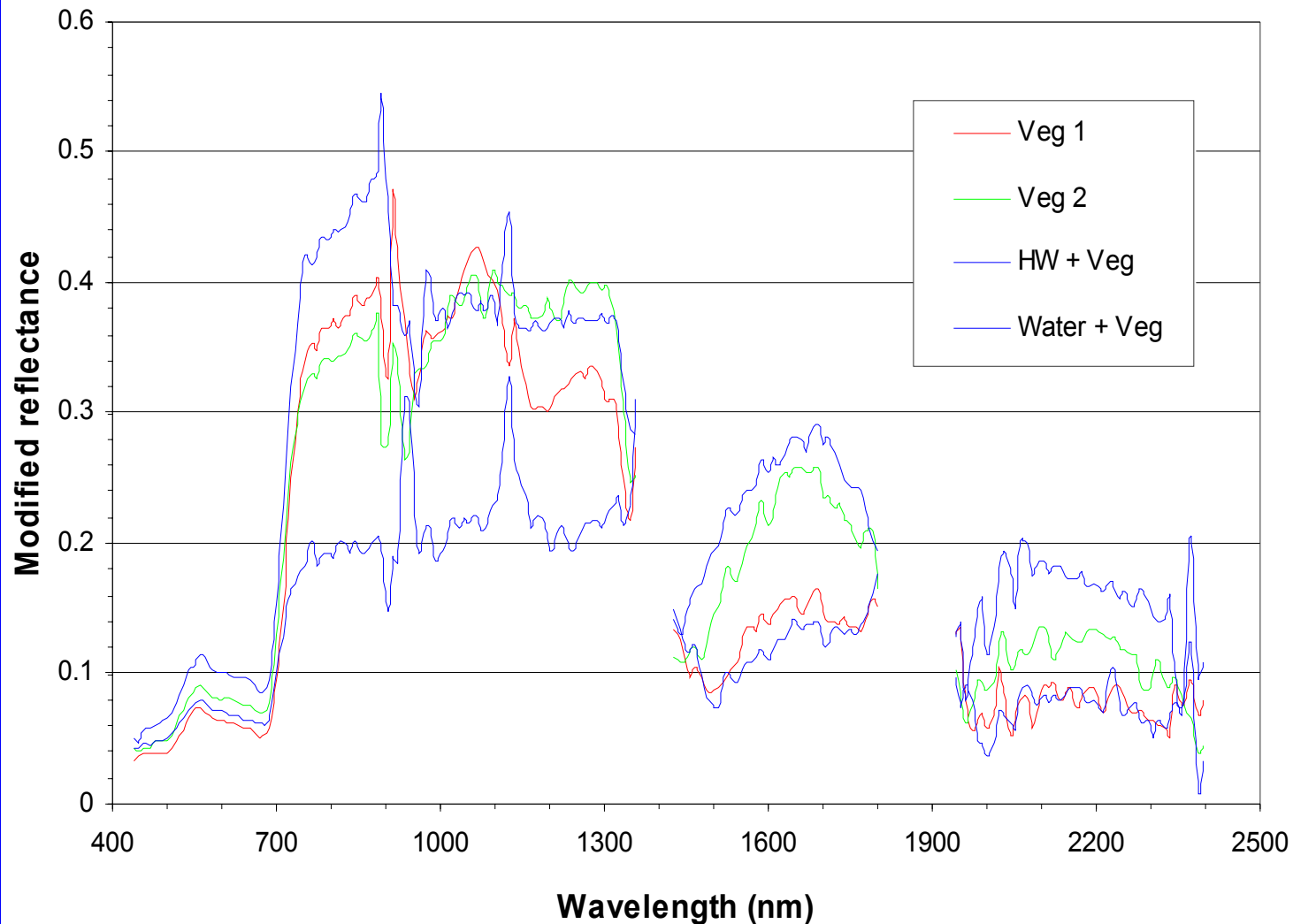
Corrected radiance of Hyperion



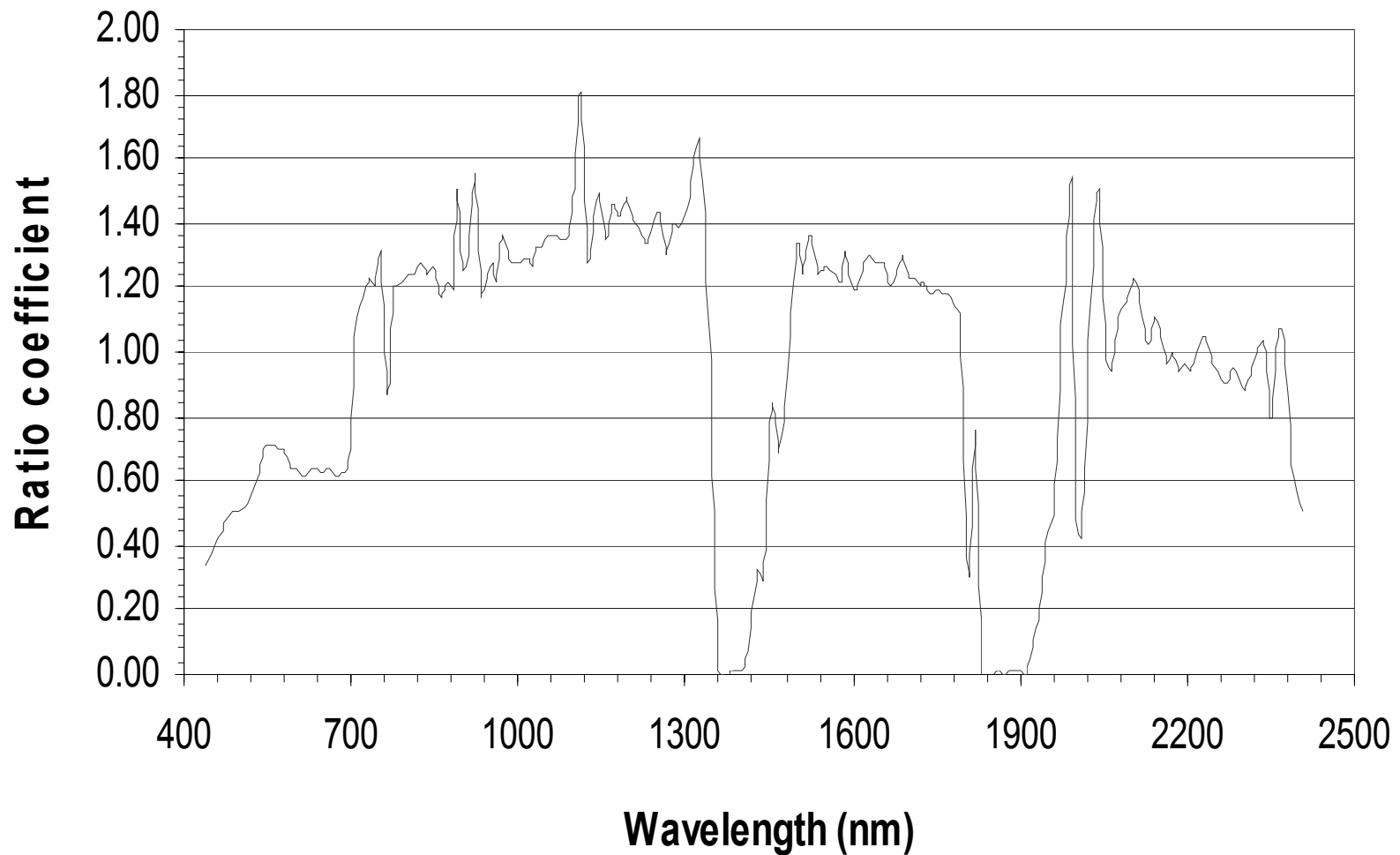
Surface reflectance retrieved from Hyperion



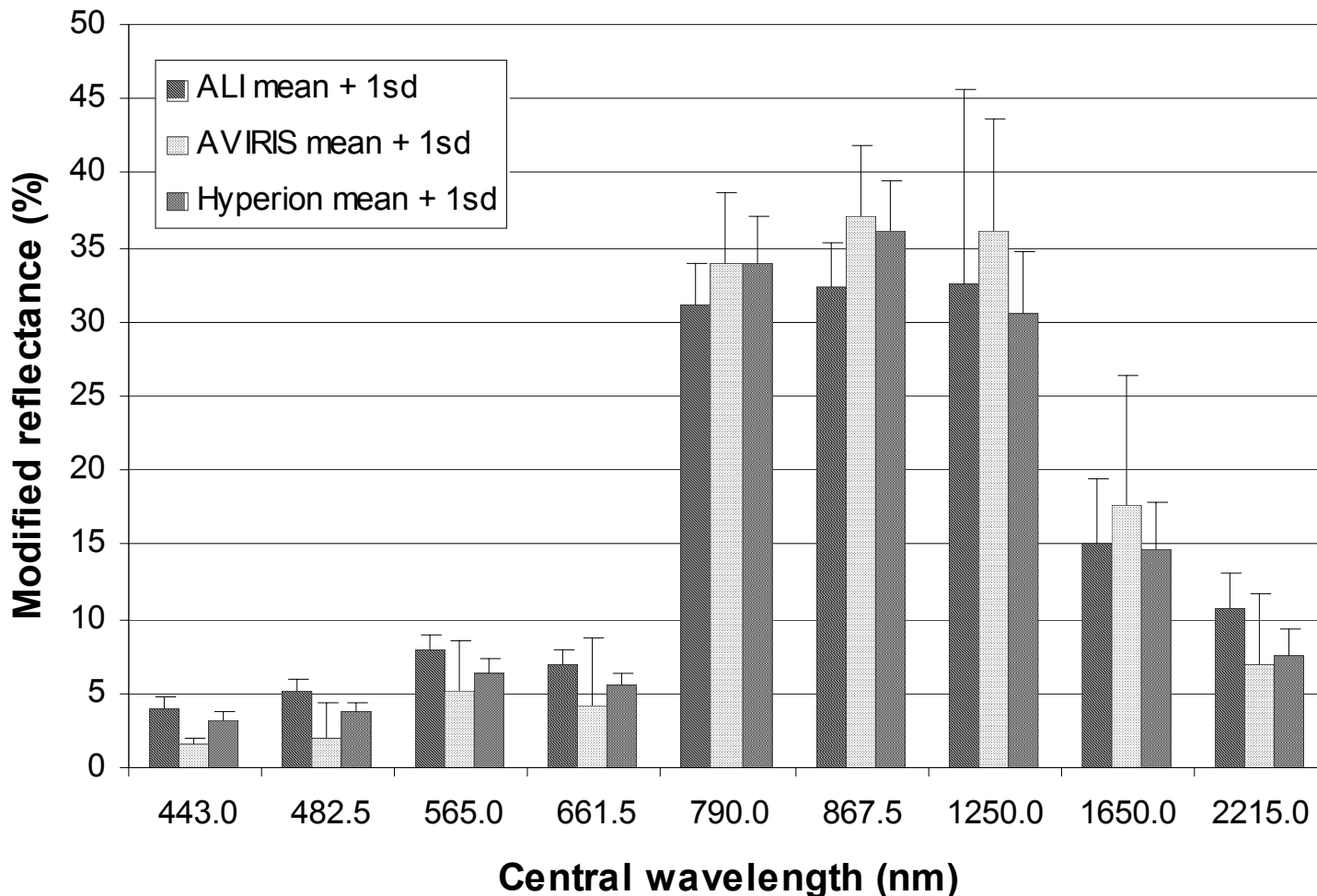
Modified surface reflectance retrieved from Hyperion



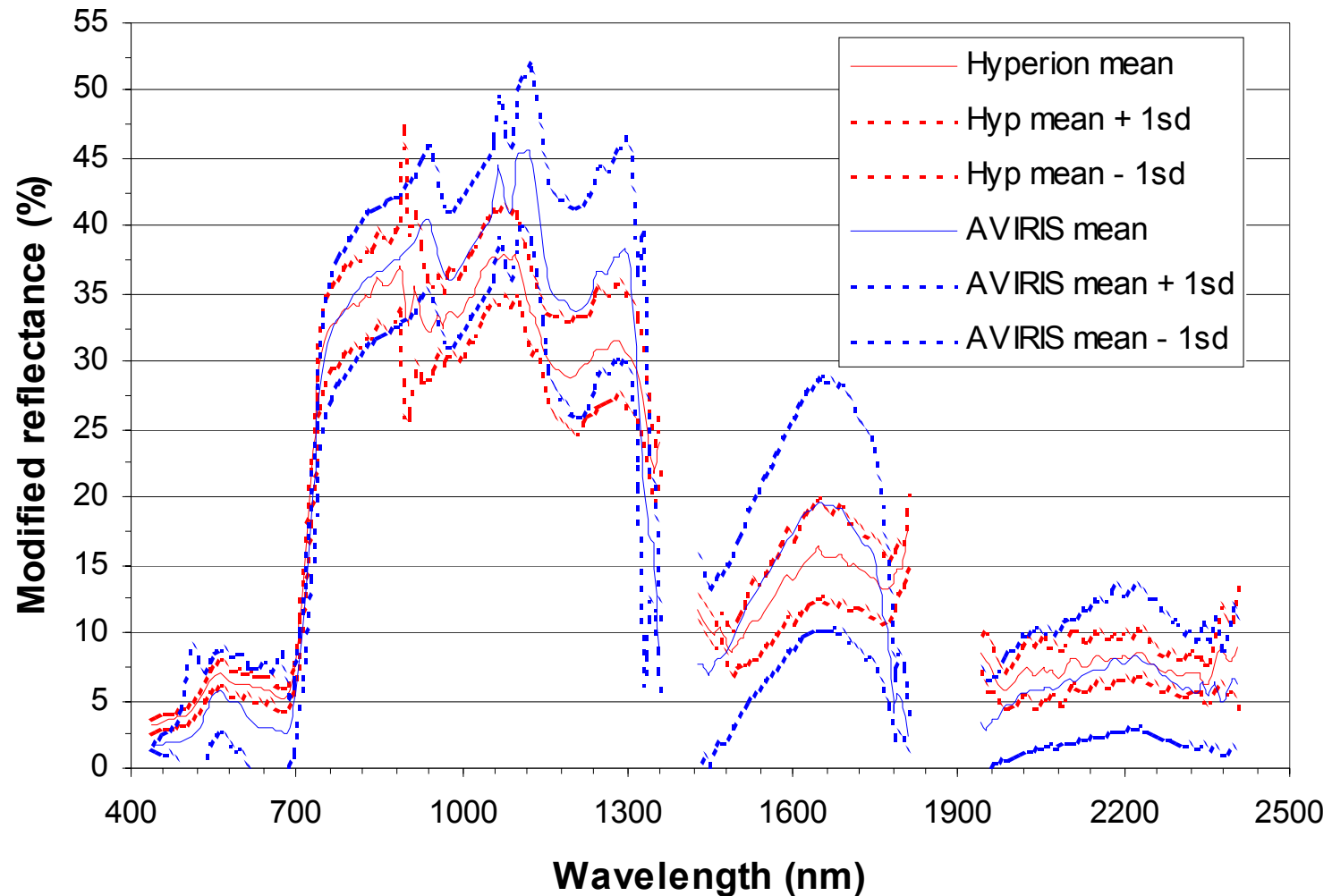
ASD ratio coefficients



Comparison of retrieved reflectances among three sensors: ALI, Hyperion and AVIRIS

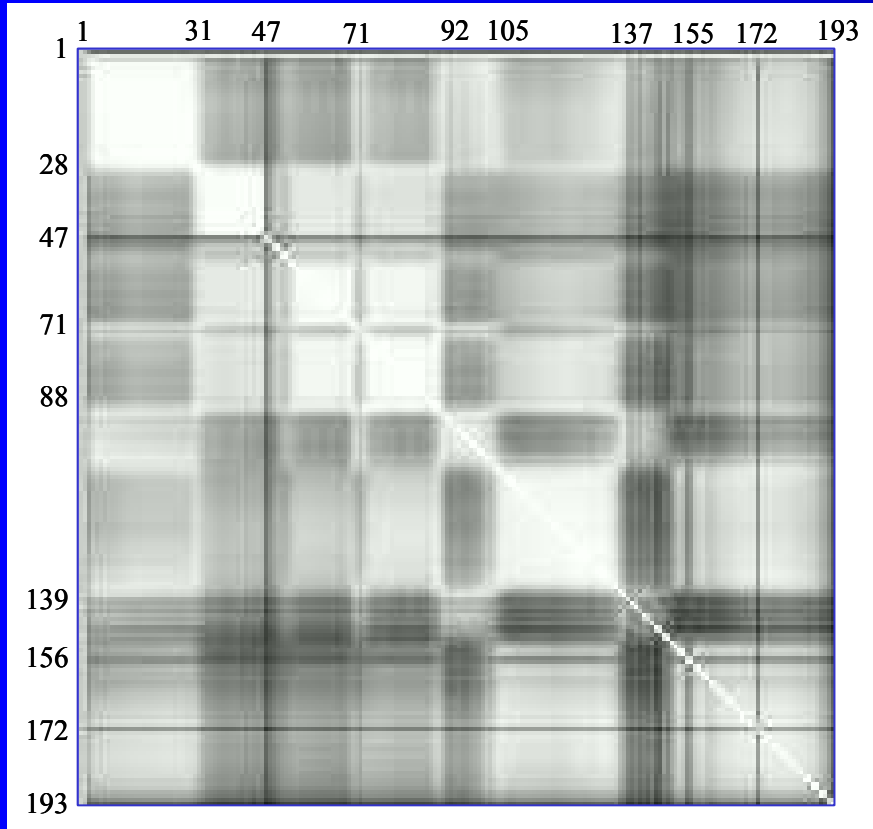


Comparison of retrieved reflectances between two sensors: Hyperion and AVIRIS



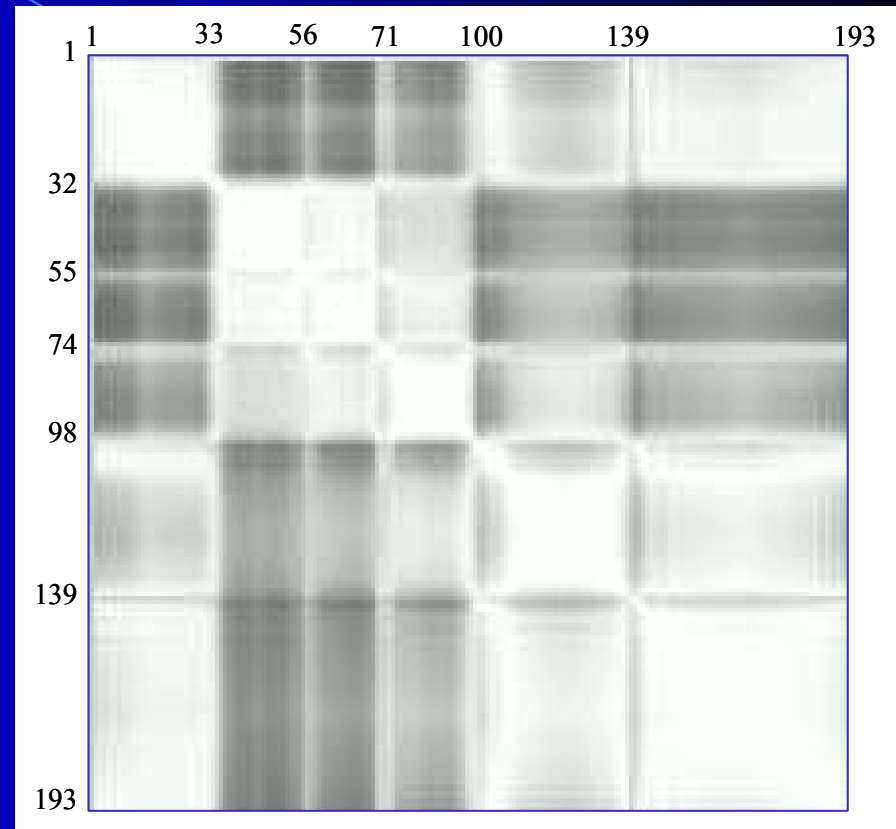
Correlograms of inter-band

Hyperion



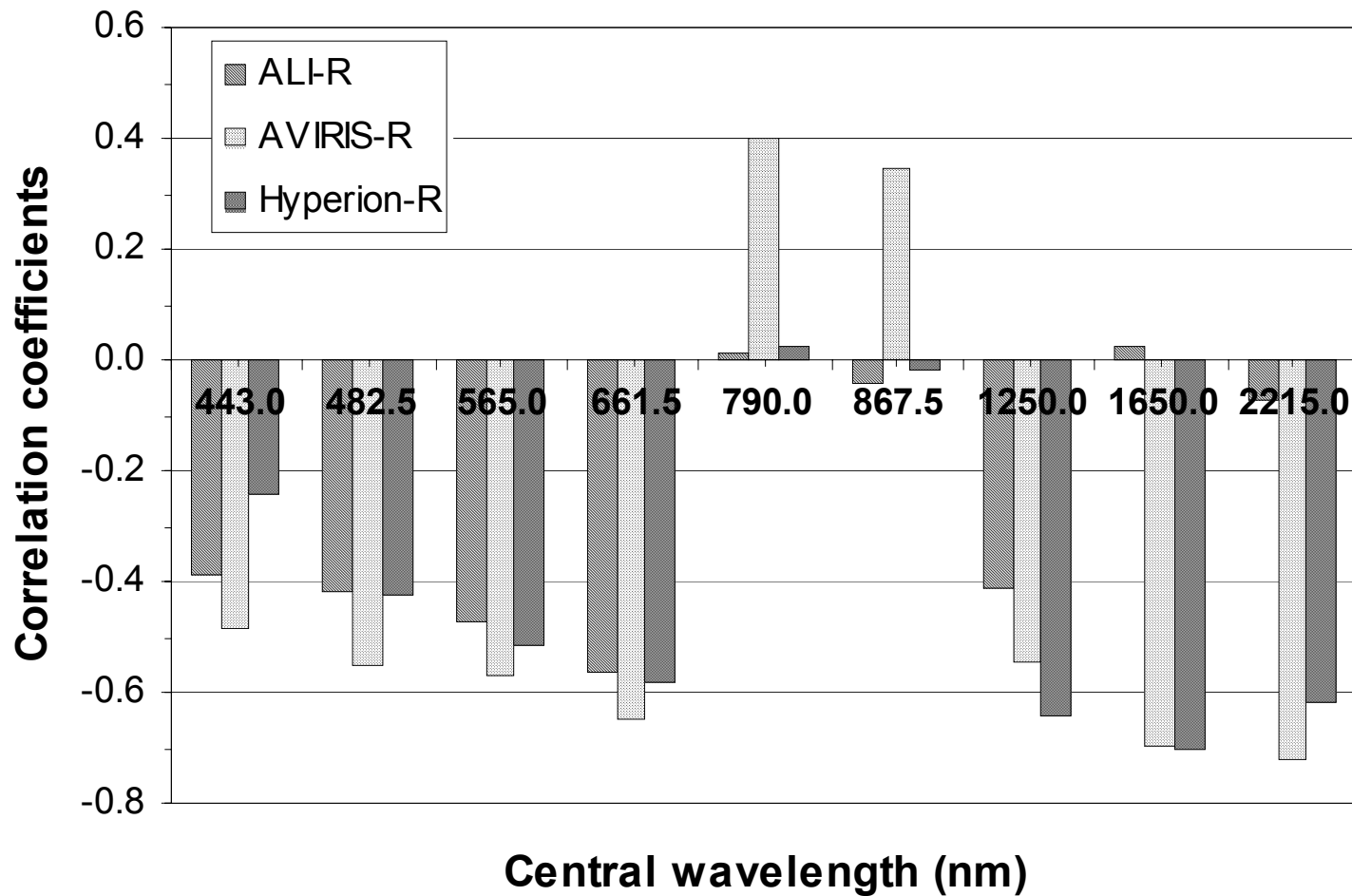
Correlogram of inter-band of Hyperion image, calculated in retrieved reflectance, 1-193 bands

AVIRIS

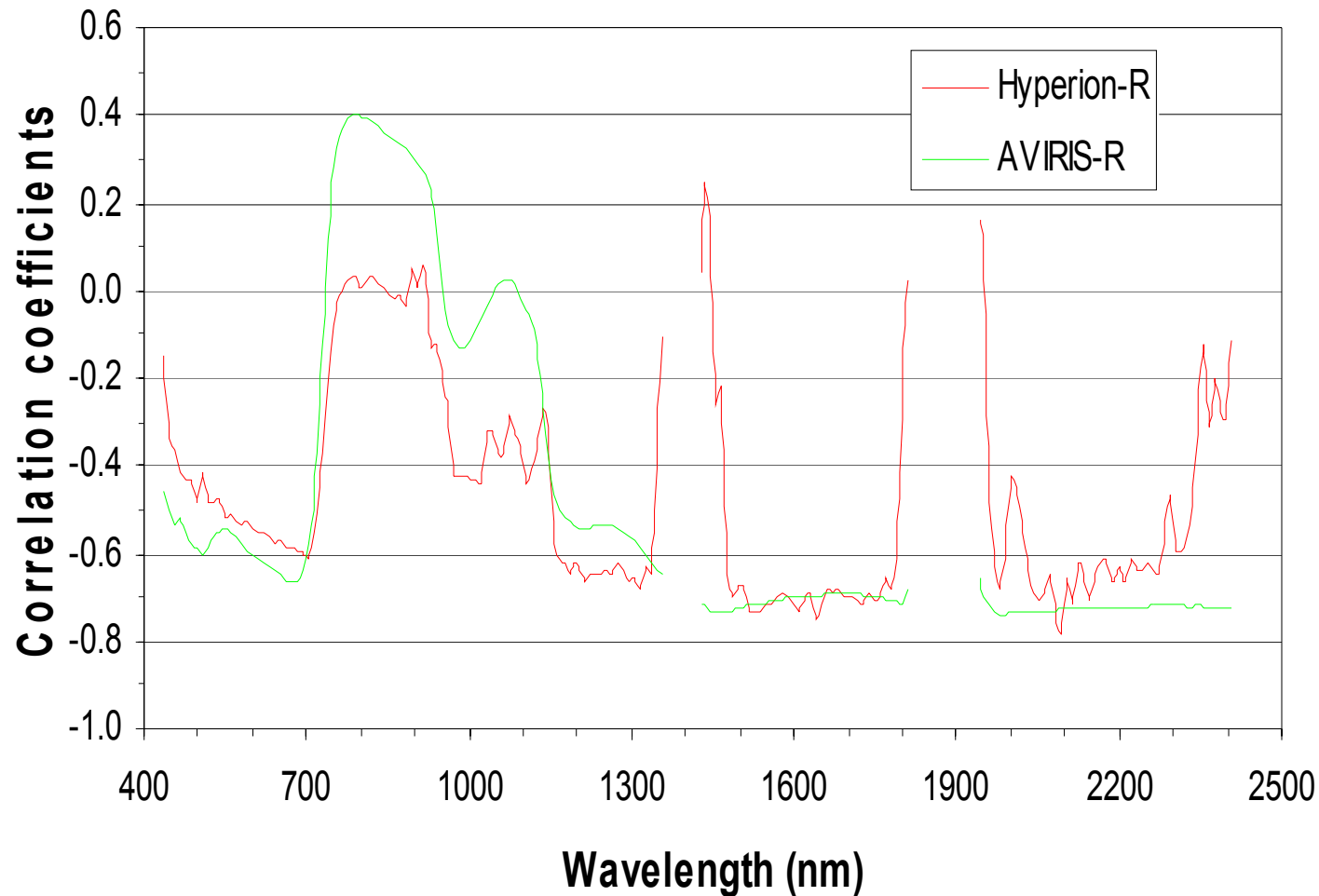


Correlogram of inter-band of AVIRIS image, calculated in retrieved reflectance, 1-193 bands

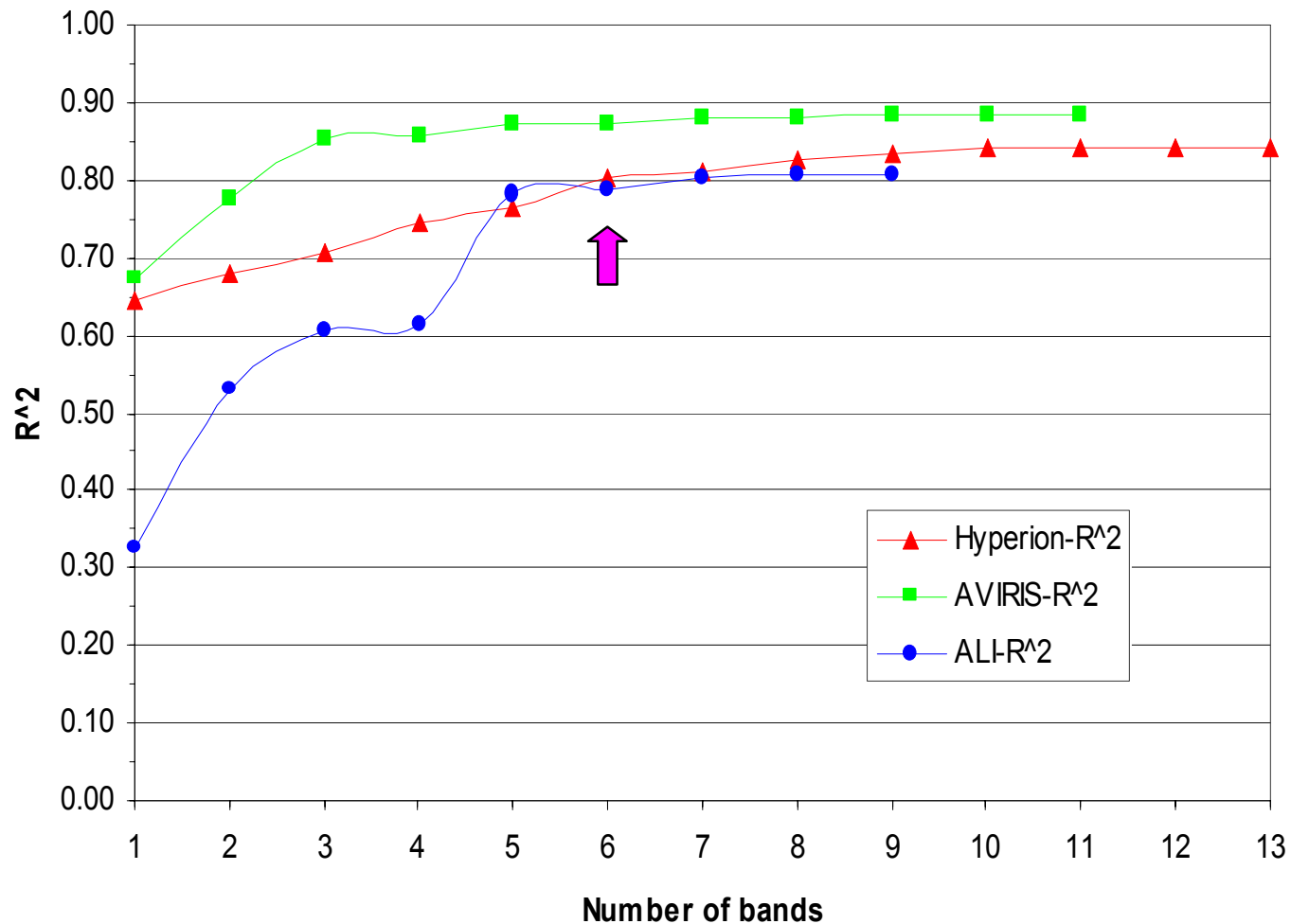
Correlation coefficients of three sensors' data with LAI



Correlation coefficients of two sensors: Hyperion and AVIRIS with LAI



Determination of 6 bands used for constructing LAI prediction models

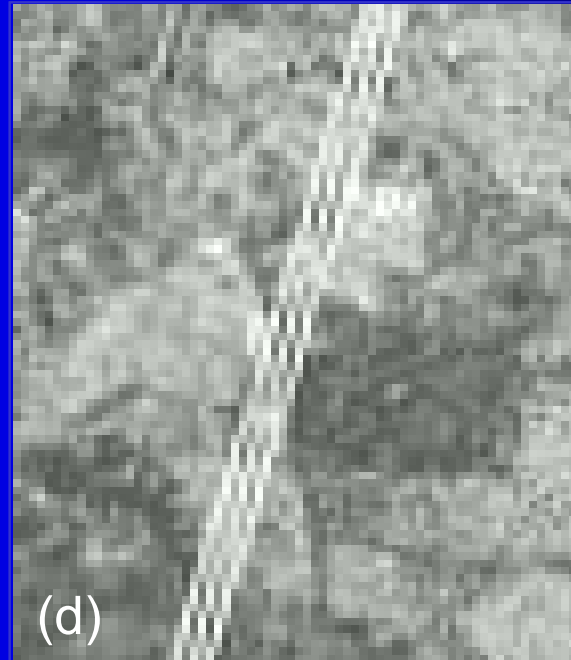
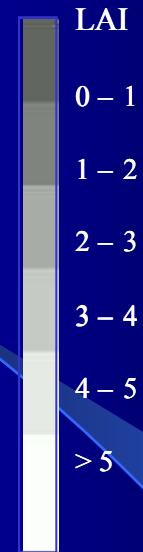
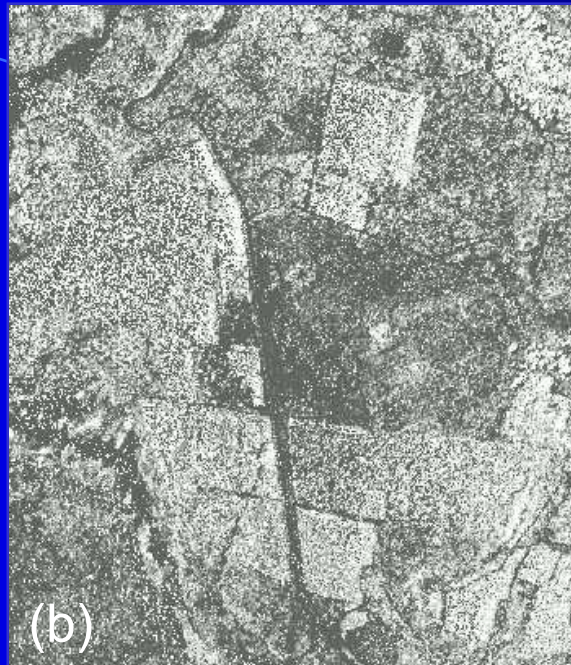
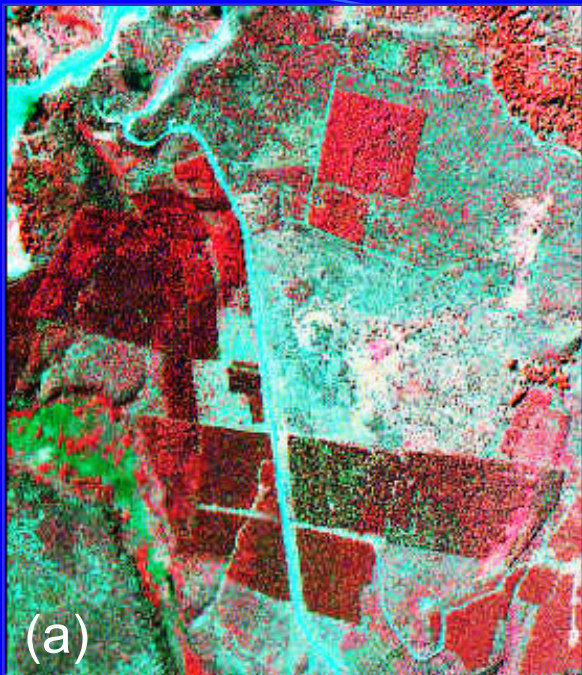


LAI prediction models using retrieved surface reflectance data from ALI, Hyperion and AVIRIS
 N = 32, 6 bands selected into the models.

	Hyperion	ALI	AVIRIS
	Log(Ref)	Log(Ref)	Log(Ref)
R^2	0.8019	0.7884	<u>0.8731</u>
Wavelengths (nm)	499, 913, 1437 1639, 2093, 2275	483, 790, 868 1250, 1650, 2215	684, 932, 1080 1991, 2261, 2400
OAA(%)	78.56	77.82	<u>82.83</u>
S.D.	0.5492	0.5679	<u>0.4397</u>

Note: OAA=overall accuracy; S.D.=standard deviation;
 all of R^2 are significant at 0.99 confident level.

LAI maps



LAI maps, (a) pseudo-color composite of AVIRIS, (b) LAI map from AVIRIS, (c) LAI map from Hyperion and (d) LAI map from ALI

12 VIs

Index	Formula	Description	References (e.g.)
SR	ρ_{NIR} / ρ_R	Near-infrared / Red reflectance ratio (Simple Ratio VI). Related to changes in amount of green biomass, pigment content and concentraion and leaf water stress etc.	Baret and Guyot, 1991; Tucher, 1979.
NDVI	$(\rho_{NIR} - \rho_R) / (\rho_{NIR} + \rho_R)$	Normalized Difference Vegetation Index. Related to changes in amount of green biomass, pigment content and concentraion and leaf water stress etc.	Fassnacht et al., 1997; Smith et al., 1991.
PVI	$\frac{1}{\sqrt{a^2 + 1}} (\rho_{NIR} - a\rho_R - b)$ a = slope of the soil line b = soil line intercept	Perpendicular Vegetation Index, orthogonal to the soil line. Attempts to eliminate differences in soil background and is most effective under conditions of low LAI, applicable for arid and semiarid regions.	Baret and Guyot, 1991; Huete et al., 1985.
SAVI	$\frac{(\rho_{NIR} - \rho_R)(1 + L)}{(\rho_{NIR} + \rho_R + L)}$ L = a correction factor	Soil Adjusted Vegetation Index. L ranges from 0 for very high vegetation cover to 1 for very low vegetation cover; minimizes soil brightness-induced variations L=0.5 can reduce soil noise problems for a wide range of LAI.	Huete, 1988; Leeuwen and Huete, 1996.
NLI	$(\rho_{NIR}^2 - \rho_R) / (\rho_{NIR}^2 + \rho_R)$	Non-Linear vegetation Index. Consider the relationship between many VIs and surface biophysical parameters is often nonlinear, and NLI linearizes relationships with surface parameters that tend to be nonlinear.	Goel and Qin, 1994
RDVI	$(\rho_{NIR} - \rho_R) / (\rho_{NIR} + \rho_R)^{1/2}$	Renomalized Difference Vegetation Index. RDVI linearizes relationships with surface parameters that tend to be nonlinear.	Roujean and Breon, 1995.
MSR	$\frac{(\rho_{NIR} / \rho_R - 1)}{(\rho_{NIR} / \rho_R)^{1/2} + 1}$	Modified Simple Ratio. It can be an improvement over RDVI for linearizing the relationships between the index and biophysical parameters.	Chen, 1996.

12 VIs (Cont'd)

Index	Formula	Description	References (e.g.)
WDVI	$\rho_{NIR} - a \rho_R$ <p>a = slope of the soil line</p>	<p>Weighted Difference Vegetation Index.</p> <p>WDVI assumes that the ratio between NIR and R reflectances of bare soil is constant; it is a mathematically version of PVI, but it has an unrestricted range.</p>	<p>Clevers, 1988; Clevers, 1991.</p>
MNLI	$\frac{(\rho_{NIR}^2 - \rho_R)(1 + L)}{(\rho_{NIR}^2 + \rho_R + L)}$ <p>L = a correction factor</p>	<p>Modified Non-linear vegetation Index. MNLI is an improved version of NLI, and it also consider merit of SAVI.</p> <p>L=0.5 may be applicable for a wide range of LAI.</p> <p>For detailed description, see text.</p>	<p>Developed in this paper.</p>
NDVI*SR	$\frac{(\rho_{NIR}^2 - \rho_R)}{(\rho_{NIR} + \rho_R^2)}$	<p>Attempts to combine merit of NDVI with that of SR.</p> <p>For detailed description, see text.</p>	<p>Developed in this paper.</p>
SAVI*SR	$\frac{(\rho_{NIR}^2 - \rho_R)}{(\rho_{NIR} + \rho_R + L)\rho_R}$	<p>Attempts to combine merit of SAVI with that of SR.</p> <p>For detailed description, see text.</p>	<p>Developed in this paper.</p>
TSAVI	$\frac{a(\rho_{NIR} - a\rho_R - b)}{[a\rho_{NIR} + \rho_R - ab + X(1 + a^2)]}$ <p>a = slope of the soil line b = soil line intercept X = adjustment factor to minimize soil noise.</p>	<p>Transformed Soil Adjusted Vegetation Index.</p> <p>Modify Huete (1988) SAVI to compensate for soil variability due to changes in solar elevation and canopy structure.</p>	<p>Baret and Guyot, 1991;</p>

Note: ρ_R and ρ_{NIR} enoted as reflectances in red and near-infrared wavelengths, but in this study, they represent band 1 and band 2 across all avaiable 193 bands of Hyperion data.

Three approaches (Cont'd)

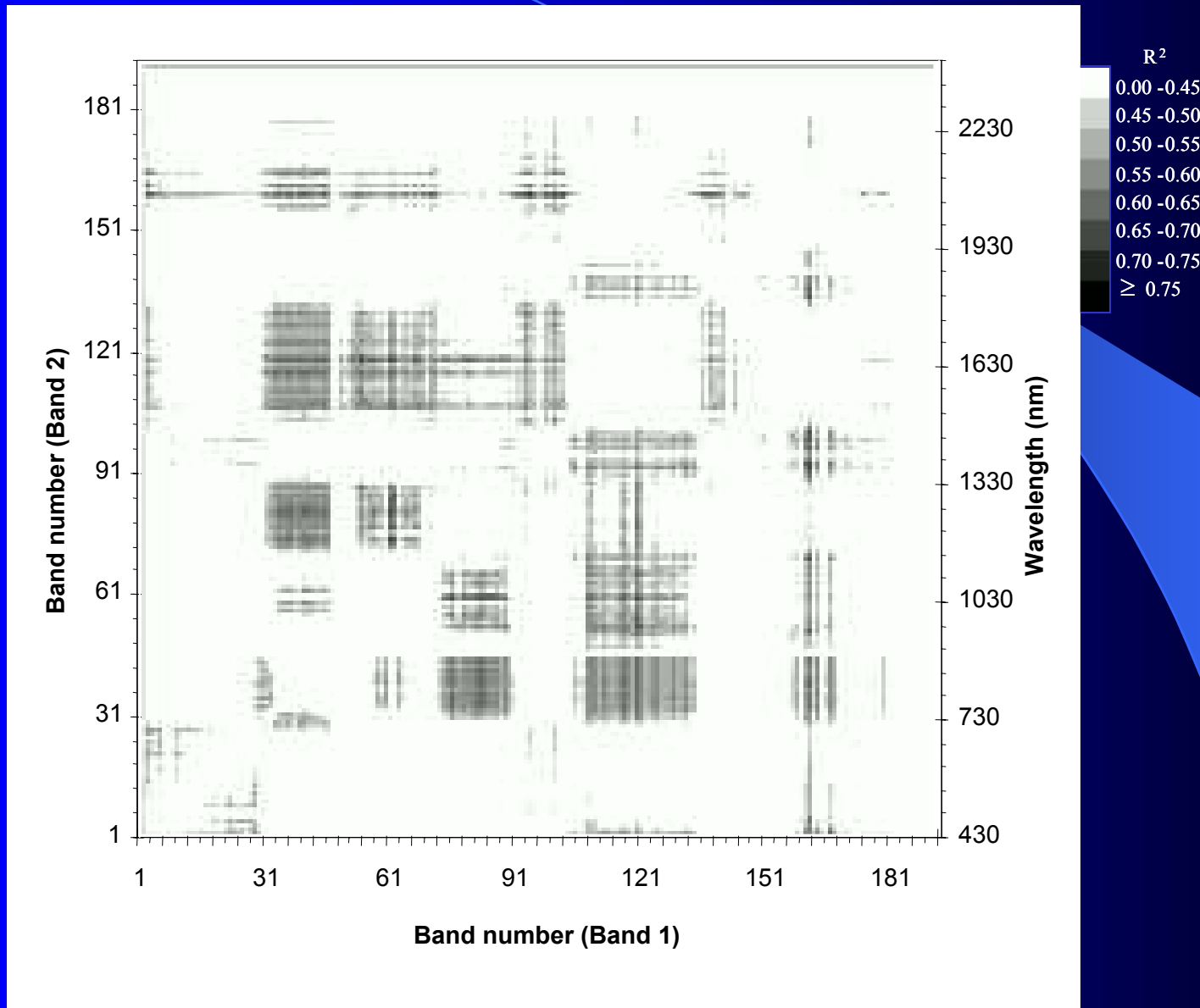
- Polynomial fitting (in fifth order)

$$\rho = a_0 + \sum_{i=1}^5 a_i \lambda^i$$

- IG red edge model, linear fitting with least square solution (Miller et al., 1990)

$$R(\lambda) = R_s - (R_s - R_0) \exp\left(\frac{-(\lambda_0 - \lambda)^2}{2\sigma^2}\right)$$

R^2 gray scale plot for SAVI vs. LAI



Potential hyperspectral bands for estimating forest LAI

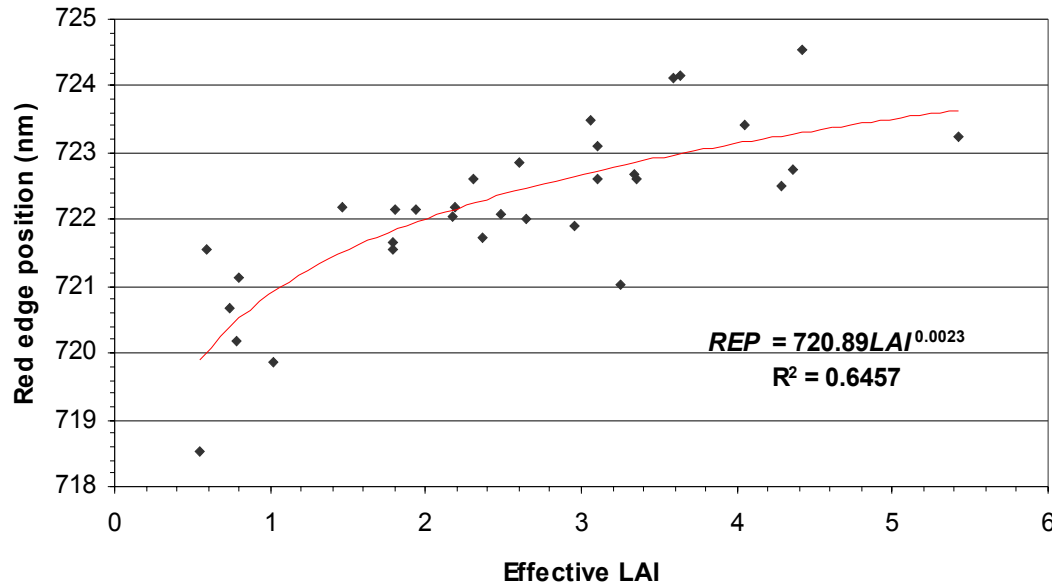
Index	R ²	Band	Bandwidth	Band description
	NIR-R/Optim.	center (nm)	(nm)	(spectral region and possible absorption features)
SR	0.55/0.70	825	140	NIR region, cell structure multi-reflected spectra.
		1038	230	NIR-SWIR region, water, protein , lignin, starch & oil absorption
		1250	180	SWIR region, water , cellulose, starch and lignin absorption
		1648	290	SWIR region, protein, nitrogen, lignin, cellulose , sugar, starch absorption.
NDVI	0.55/0.70	4 bands similar to SR's
PVI	0.45/0.64	814	140	NIR region, cell structure multi-reflected spectra.
		1050	100	NIR-SWIR region, protein , lignin, and oil absorption
		1250	190	SWIR region, water , cellulose, starch and lignin absorption
		2100	10	SWIR region, starch , cellulose absorption
SAVI	0.50/0.67	4 bands similar to NDVI's or SR's
NLI	0.50/0.73	821	157	NIR region, cell structure multi-reflected spectra.
		1200	578	NIR-SWIR region, water , protein, starch, lignin, cellulose, and oil absorption
		1250	191	SWIR region, water , cellulose, starch and lignin absorption
		1640	300	SWIR region, protein, nitrogen, lignin, cellulose , sugar, starch absorption.
RDVI	0.45/0.66	810	170	NIR region, cell structure multi-reflected spectra.
		1054	10	SWIR region, lignin and oil absorption
		1255	161	SWIR region, water , cellulose, starch and lignin absorption
		1669	10	SWIR region, lignin and starch absorption
		2093	10	SWIR region, starch and cellulose absorption

Potential hyperspectral bands for estimating forest LAI (Cont'd)

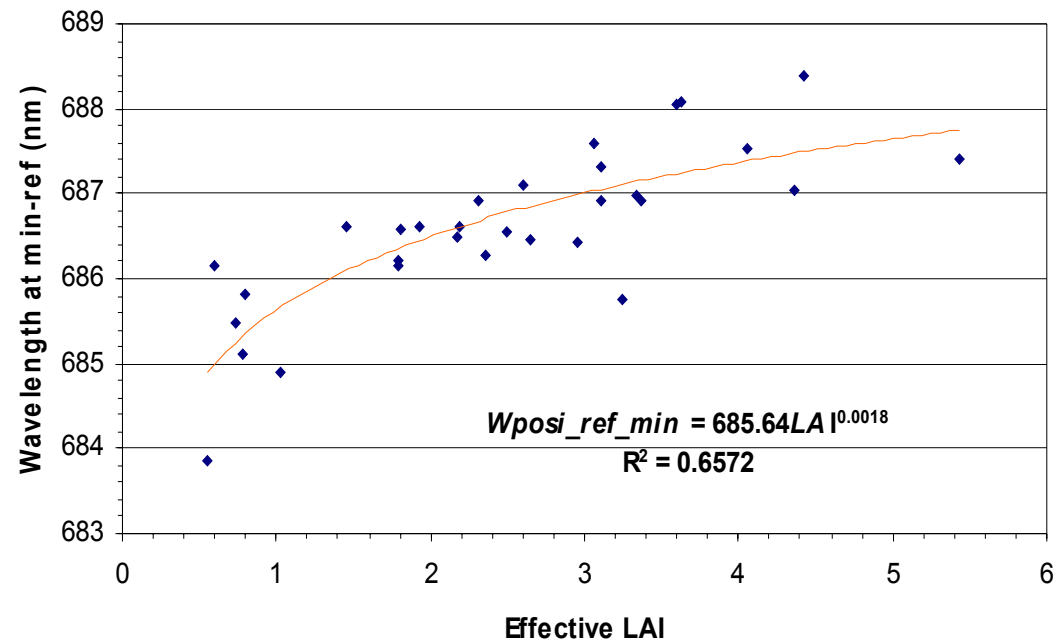
Index	R ² NIR-R/Optim.	Band center (nm)	Bandwidth (nm)	Band description (spectral region and possible absorption features)
MSR	0.50/0.70	4 bands similar to NDVI's or SR's
WDVI	0.45/0.63	1377	10	SWIR region, water absorption
		1427	10	SWIR region, lignin absorption
		1639	10	SWIR region, non apparent absorption
		2113	10	SWIR region, starch and cellulose absorption
		2285	30	SWIR region, starch, cellulose and protein absorption
MNLI	0.45/0.75	4 bands similar to NLIs
NDVI*SR	0.50/0.71	4 bands similar to NDVI's or SR's, but
SAVI*SR	0.50/0.71	1 - 4 bands similar to SAVI's or SR's
		2083	30	SWIR region, sugar, starch and cellulose absorption
		2153	10	SWIR region, protein absorption
TSAVI	0.50/0.71	832	120	NIR region, cell structure multi-reflected spectra.
		1038	150	NIR-SWIR region, water , proten , lignin, starch & oil absorption
		1240	170	SWIR region, water , lignin, cellulose and starch absorption
		1660	260	SWIR region, lignin , cellulose , sugar , starch, protein, and nitrogen absorption.
		2108	20	SWIR region, starch , cellulose and protein absorption

Note: Optim. = optimal correlation R²; **bold chemicals** are principal for the absorption features

4-point approach



Forest LAI vs. two red edge parameters extracted with 4-point interpolating approach (using bands 671.62, 702.12, 742.80, and 783.48 nm).
Upper: LAI versus red edge position; right: LAI versus red well (minimum reflectance position)



Conclusions

- The method of atmospheric correction used in this study is promising but needs refinement.
- LAI prediction model derived from AVIRIS has the highest correlation and lowest regression SD, followed by Hyperion and ALI
- Since atmospheric effects on VNIR more than SWIR, more potential in SWIR with Hyperion.
- Atmospheric correction is critical for hyperspectral data application, especially in VNIR region

Conclusions cont'd

- Most of the important bands with high R^2 related to bands in SWIR region and some in NIR region.
- The bands centered near 820, 1040, 1200, 1250, 1370, 1430, 1650, 2100, 2260 nm with bandwidths from 10 to 300 nm are important for constructing VIs for estimating LAI.
- The 4-point approach is a more practical application method to extract two red edge parameters because only 4 bands are considered for use
- It is notable that the originally defined VIs with R and NIR bands did not produce higher correlation with LAI than VIs constructed with bands in SWIR region.
- Atmospheric correction is critical for hyperspectral data application, especially for VNIR region

Acknowledgments

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- Assistance in field work by Gillsermo Defossé, Florencia Farias, and Maria Cristina Frugoni is appreciated.